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Financial Constraints: Routine Versus Cutting Edge R&D Investment

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Non-technical Summary

Investment in research and development (R&D) is usually considered to be subject to financing constraints due to outcome uncertainty leading to asymmetric information between borrowers and lenders. Moreover, R&D investment typically has a low inside collateral value as it is sunk once expensed. These arguments on market failures are often used to justify governmental intervention in the market for R&D through subsidy grants and tax credits. While the empirical literature on detecting financial constraints for R&D is vast, results are often ambiguous. We argue that the inconclusiveness may be due to heterogeneity among R&D investments that has been neglected in previous literature.

We account for such heterogeneity of R&D investments by grouping the sample into potentially constrained and unconstrained firms based on Kamien and Schwartz (1978). According to this distinction, the former -*defensive R&D*- firms, are less likely to face financial constraints for their activities than the latter -o*ffensive R&D*- firms. Since large innovations involving basic research require significantly more resources, are much riskier in terms of default and expected returns, and are more prone to secrecy issues, the acquisition of external capital may be curtailed. If this applies empirically, it has strong implications for innovation policy. As cutting-edge innovations are typically seen as the driving force of technological progress and long-term growth, it is questionable whether current policy practice aimed at alleviating financial constraints indeed addresses this type of R&D.

We implement this test on financial constraints empirically by investigating R&D investments of product innovators, where the type of R&D with respect to the degree of innovativeness is considered as being decisive for financial constraints. On the one hand, we define firms pursuing cutting-edge R&D as those that aim at introducing market novelties. The control group of routine R&D performers consists of firms that mainly aim at improving existing products or pure imitation.

Furthermore, this study accounts for a widely discussed methodological critique formulated by Kaplan and Zingales (1997) on earlier studies. They question the approach of identifying financial constraints by estimating investment-cash flow relationships and call for further research where financial constraints are not identified indirectly through investment-cash flow sensitivities, but observed more directly. Our contribution follows this by making use of a credit rating index which constitutes a direct observation of expected credit market constraints.

Using panel data, we show that firms pursuing cutting-edge R&D strategies are subject to financial constraints in the credit market. Our indicator, a credit rating index, turns out to curtail R&D spending for cutting-edge R&D while it does not for routine R&D investment. Moreover, we complement the finding of Kaplan and Zingales (1997) that the investment-cash flow sensitivity is not monotonically increasing with the level of constriction by identifying such a monotonic relationship between the credit rating index and R&D investment.

This finding has important implications for innovation policy. We can assume that cutting-edge innovations are the driving force of technological progress, and thus yield higher social returns than routine R&D projects in the long run. Our results, however, show that such investments are subject to binding credit market constraints. This may call for policy measures towards cutting-edge R&D projects. It would be interesting for further research to investigate whether current policies address those investments. In many European countries, it is current practice that grant proposals for public R&D funding are evaluated with respect to expected economic returns and technological feasibility. It may apply exactly to cutting-edge research, though, that expert reviewers consider daring and visionary projects as not feasible or too uncertain, so that public subsidies may not be granted. If so, projects with potentially high social returns may be judged as inferior to more routine R&D projects.

Financial constraints:
routine versus cutting edge R&D investment*

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Abstract

We analyze financial constraints for R&D, where we account for heterogeneity among investments which has been neglected in previous literature. According to economic theory, investments should be distinguished by their degree of uncertainty, e.g. routine R&D versus cutting-edge R&D. Financial constraints should be more binding for cutting-edge R&D than for routine R&D. Using panel data we find that R&D spending of firms devoting a significant fraction of R&D to cutting-edge projects is curtailed by credit constraints while routine R&D investments are not. This has important policy implications with respect to the distribution of R&D subsidies in the economy.

Keywords: R&D, Financial Constraints, Panel Data
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1 Introduction

Investment in research and development (R&D) is usually considered to be subject to financing constraints due to outcome uncertainty leading to asymmetric information between borrowers and lenders (Arrow 1962, Nelson 1959, Hall et al. 1992, Lach and Schankerman 1988, Harhoff et al. 1999 and Mansfield et al. 1977). Moreover, R&D investment typically has a low inside collateral value as it is sunk once expensed. These arguments on market failures are often used to justify governmental intervention in the market for R&D through subsidy grants and tax credits. While the empirical literature on detecting financial constraints for R&D is vast (see Hall, 2002, for a survey), results are often ambiguous[1]. However, these studies may deliver inconclusive results due to the conceptual set-up of many empirical studies or limitations in data availability. In many of these studies only large, stock market listed firms are being considered (see for example Scherer 1965, Mueller 1967, Elliot 1971). Yet, we argue that the inconclusiveness may be due to heterogeneity among R&D investments that has been neglected in previous literature.

In a theoretical model, Kamien and Schwartz (1978) distinguish firms doing routine R&D to strengthen their established product lines and firms investing in more fundamental R&D projects aiming at more radical market innovations. According to this distinction, the former -*defensive R&D*- firms, are less likely to face financial constraints for their activities than the latter -o*ffensive R&D*- firms. Since large innovations involving basic research require significantly more resources, are much riskier in terms of default and expected returns, and are more prone to secrecy issues, the acquisition of external capital may be curtailed. If this applies empirically, it has strong implications for innovation policy. As cutting-edge innovations are typically seen as the driving force of technological progress and long-term growth, it is questionable whether current policy practice aimed at alleviating financial constraints indeed addresses cutting-edge type R&D.

[1] For example, Chiao (2002) finds a negative influence of debt on R&D spending in science-based industries, but a positive one in non-science based industries indicating that risk is significantly lower in the latter. Hall (1992), Himmelberg and Petersen (1994), Harhoff (1998) find a positive relationship between R&D and cash flow for the U.S. Bond et al. (2006) find that cash flow predicts whether a firm does R&D or not in the UK, but not the level of R&D indicating that UK firms that do R&D are a self-selected group that face fewer constraints. Yet, they find no such effects for Germany. Mulkay et al. (2001) find that cash flow impacts more in the U.S. than in France both for R&D and ordinary investment. Baghat and Welch (1995) found similar results for the U.S. and U.K. as well as Bougheas et al. (2003) for Ireland (see Hall 2002 for a survey).

We implement this test on financial constraints empirically by investigating R&D investments of product innovators, where the type of R&D with respect to the degree of innovativeness is considered as being decisive for financial constraints. On the one hand, we define firms pursuing cutting-edge R&D as those that aim at introducing market novelties. The control group of routine R&D performers consists of firms that mainly aim at improving existing products or pure imitation. We argue that cutting-edge R&D performers may well follow more risky investment strategies than others. Therefore, we believe that this is an empirical approximation of the notion of risky investment behavior as indicated in the theoretical model by Kamien & Schwartz (1978).

Furthermore, this study accounts for a widely discussed methodological critique formulated by Kaplan and Zingales (1997). Due to the specific characteristics of R&D investment, scholars argued that firms have to rely to a great extent on internal sources of financing for their R&D projects. Thus, firms regarded as unconstrained or less constrained are those with relatively high liquidity. In a seminal paper, Fazzari et al. (1988) suggest to investigate financial constraints by estimating investment-cash flow relationships. For this, they grouped their sample of firms into potentially unconstrained and constrained firms according to dividend pay-outs. If the investment of the potentially constrained group is more sensitive to internal financial resources than that of the other, one would conclude that the credit market would curtail investments of these firms. This methodology has been adopted by many subsequent studies (see the survey by Hall, 2002).

Kaplan and Zingales (1997) heavily criticized this methodological approach, though. Using the potentially constrained firms of the study by Fazzari et al. (1988), they show that the investment-cash flow relationship may not be appropriate to judge about financial constraints. Kaplan and Zingales split the sample into different groups of firms ranging from definitely constrained to not constraint firms. Rather than using an ad-hoc grouping, they created ratings by carefully combining annual report data with qualitative evidence from management reports on liquidity and other sources. They show that the investment-cash flow sensitivity is not monotonically increasing with the level of constriction. Hence, this study places high doubts on earlier research and, consequently, calls for further research where financial constraints, are not identified indirectly through investment-cash flow sensitivities, but observed more directly.

> “The final implication of our paper is a methodological one. Our research design and results point out what we think is a weakness in existing research as well as

> an opportunity for future research. A great deal can be learned trough more direct observation." (Kaplan and Zingales, 1997: p. 212).

Our contribution follows the advice of Kaplan and Zingales (1997) by making use of a credit rating index which constitutes a direct observation of expected credit market constraints. The credit rating index is generated by Germany's largest rating agency and serves us as indicator of firms' ability to raise external funds for their R&D investment.[2]

To sum up, we estimate an equation such as R&D = f(Credit Rating, Controls) for firms conducting cutting-edge R&D (RISK = 1) and those performing more routine R&D (RISK = 0). Note that this grouping is *not* related to the idea of Fazzari et al. (1988) who need to split the sample in order to identify financial constraints through different cash flow-investment sensitivities. We observe the level of constriction directly through the credit rating, which is a continuous measure (an index from 100 to 600). If we were only interested in the question if and to what extent credit market restriction curtail firm level investment, we would not split the sample, but simply run regressions in the total sample. The effect of credit constraints would be identified through the variation in the rating variable and its estimated coefficient. However, as we follow Kamien and Schwartz who argue that potential credit market restrictions are less binding for routine R&D investments than for cutting-edge R&D investments, we split our sample in two groups to account for the heterogeneous nature of R&D investments.

We show that firms pursuing cutting-edge R&D strategies are subject to financial constraints in the credit market. Our indicator, a credit rating index, turns out to curtail R&D spending for cutting-edge R&D while it does not for routine R&D investment. Moreover, we complement the finding of Kaplan and Zingales (1997) that the investment-cash flow sensitivity is not monotonically increasing with the level of constriction by identifying such a monotonic relationship between the credit rating index and R&D investment.

Section 2 presents the database and variables, section 3 set-up and results of the empirical analysis. Section 4 concludes.

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[2] See Czarnitzki and Kraft (2007) for an analysis of the usefulness of credit rating information. Czarnitzki (2006) provides evidence on the relationship between R&D policy (subsidies) and financial constraints in small and medium enterprises using credit rating information.

2 Data and empirical set-up

Our data stem from the Mannheim Innovation Panel (MIP) which is an annual survey in the German business sector conducted by the Centre for European Economic Research (ZEW), Mannheim. The MIP started in 1992 as German part of the European-wide Community Innovation Survey with the aim to provide key innovation data for policy and research purposes. The survey identifies process and product innovators as well as non-innovative firms in manufacturing and service industries. Our study uses the survey from the manufacturing sector. The subsample of product innovators allows us to implement the theory derived distinction of defensive versus offensive R&D. Product innovative firms can be differentiated into original innovators and imitators. Imitators are those firms that indicate to introduce new products that were only new to the firms' product portfolio but that were not new to the market (RISK = 0). Original inventors, on the contrary, introduce market novelties.

How to define a cutting-edge R&D performer? We split the sample according to the distribution of the sales share achieved with market novelties (*NOVEL*) at the firm level averages (not based on firm-year observations). 38% of product innovators are pure imitators, i.e. their sales with market novelties are always zero. The median of *NOVEL* amounts to 2.5%, and the 75% quantile of the distribution is at a novelty sales share of 7.5%. We estimated several versions of our models. The subsequently presented results are based on a 1/3 versus 2/3 sample split: a product innovator is defined as cutting-edge R&D performer (RISK = 1) if *NOVEL* > 5% of total sales during our observed time period, on average. The other group is denoted as RISK = 0. Note, however, that other definitions, such as sample split at 2.5% (at the median) or 7.5% (at the 3rd quartile) result in the same conclusions (see appendix).

Our sample covers the 1993 to 2002 period. We have an unbalanced panel of 1,252 firm-year observations (354 different firms) on firms following cutting-edge R&D investment strategies (*NOVEL* > 5%) and are thus more prone to be financially constrained than our control group. The latter consists of 2,642 firm-year observations (742 different firms) on firms devoting most of their innovation effort towards imitation. The panel is unbalanced. While the data cover a time period of 10 years, 40% of firms are observed only two or three times in the panel, another 40% are observed between four and six times, and the final 20% more frequently (up to nine times).

Note that we use a sample which is more representative of the economy than those used in several earlier studies, where scholars had to restrict their analysis to large R&D-performing firms due to limitations in data availability. Due to a large fraction of small firms (median size = 180 employees; a quarter of firms is smaller than 55 employees), firms may not conduct R&D in every year. We take this censoring of the dependent variable into account by estimating censored regression models (Tobit). Due to the skewness of the distribution, we use R&D expenditure measured as ln(1+*R&D*) as dependent variable in all regressions.[3]

The most important right-hand side variable is the credit rating reflecting access to external capital. The credit rating is an index between 100 and 600, where an index of 600 indicates the worst rating (*RATING*).

While we do not rely on the identification of constraints through investment-cash flow relationships, we still control for the availability of internal funds. The most commonly used measure of internal financial resources is cash flow. As our sample, however, is not limited to large firms which are obliged to publish balance sheet information, we have no cash flow information. Instead, we calculate the empirical price-cost margin as

$$PCM = \frac{(Sales \text{ - } Staff\ Cost \text{ - } Material\ Cost + \delta \cdot R\&D)}{Sales},$$

which has been used widely in the literature (e.g. Collins and Preston 1969, Ravenscraft 1983). Since R&D is an expense, the decision to invest in R&D will decrease *PCM* in the corresponding period. As we want to measure internally available funds during the year irrespective of the actual decision on investment, it is common to add the R&D expenses back into *PCM* (cf. Harhoff 1998). As *PCM* does not account for capital cost, we only add the staff and material cost shares of R&D. These amount to 93% ($\delta = 0.93$) according to the Wissenschaftsstatistik (1999) which is the official German R&D statistic.

Further control variables are firm size measured by the number of employees (*EMP*) and the capital intensity (*KAPINT* = tangible assets / *EMP*) as capital intensive firms may conduct more R&D as they rely more on technological improvements than labor intensive producers. Furthermore, capital may serve as collateral in credit negotiations with potential lenders, facilitating access to external sources of financing. We also use firms' age (AGE) to control

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[3] R&D expenditure is measured in million "Deutsche Mark" (1 DM $\approx$ 0.51 EUR).

for age-related effects, e.g. younger firms may conduct more R&D ceteris paribus than older firms as those could have more established products in the market. Finally, a set of 8 time dummies controls for business cycle effects, and 10 industry dummies (only included in pooled cross-sectional regressions) control for variation of R&D intensity across sectors. We use lagged values of all time variant variables (except age) to avoid direct simultaneity between R&D and explanatory variables.

Descriptive statistics for both groups (RISK = 0 and RISK = 1) are presented in Table 1. The firms in the RISK = 0 group are on average 52 years old, while the RISK = 1 firms are slightly younger (about 47 years). However, the firms in the latter group are bigger in terms of average employment, e.g. 621 compared to 478 in the RISK = 0 group. Firms in both groups show about the same capital intensity. Furthermore, we see that those firms following a – according to our definition - more risky R&D strategy indeed spend considerably more on R&D than the control group. Moreover, Table 1 show those firms have a slightly higher price-cost-margin the firms in our non-risky control group.[4]

Table 1: Descriptive Statistics

Variable	**RISK = 0** (2,642 obs.)				**RISK = 1** (1,252 obs.)			
	Mean	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
$R\&D_{it}$	3.736	29.269	0	866.739	11.556	73.548	0	1,291.094
$EMP_{i,t-1}$	477.712	1,450.847	2	28,400	621.014	2,007.068	3	47138
$KAPINT_{i,t-1}$	0.089	0.098	0.001	0.791	0.083	0.093	0.002	0.799
$PCM_{i,t-1}$	0.270	0.150	-0.377	0.814	0.304	0.159	-0.338	0.825
AGE_{it}	52.168	42.274	1	202	46.666	40.807	0	186
$RATING_{it-1}/100$	2.004	0.580	1	6	1.968	0.426	1	6

Note: time and industry dummies omitted.

3 Econometric Analysis

We employ three different models to our panel data, a pooled cross-sectional approach, a random effects estimator and a modification of the latter by Wooldridge (2002). The model can be written as

[4] The relatively large difference of average R&D spending between groups is to a large extent due to a few huge firms that spent more than 100 million Deutsche Mark on average. Taking those out of the sample, does not alternate any of the findings.

$$y_{it} = \max\left(0, x_{it}\beta + c_i + u_{it}\right), \quad i = 1,2,\ldots,N, \;\; t = 1,2,\ldots,T$$
$$u_{it} \mid x_i, c_i \sim N\left(0, \sigma_u^2\right)$$

where y_{it} is the dependent variable, x_{it} denotes the set of regressors, β the parameters to be estimated, and c_i the unobserved firm-specific effect, and u_{it} is the error term. We estimate three versions of this model. First, we assume that $c_i = 0$, and thus the model can be estimated as a simple pooled cross-sectional model, where we adjust the standard errors for firm clusters to account for the panel structure of the data. Thus, we allow the error terms to be correlated within firm observations. The pooled model has the advantage that it is not necessary to maintain the strict exogeneity assumption. While u_{it} certainly has to be independent of x_{it}, the relationship between u_{it} and x_{is}, $t \neq s$, is not specified (see Wooldridge, 2002: 538). Hence, the model allows, for instance, for feedback of R&D in period t to the regressors in future periods. In the second version of the model, we apply a random-effects Tobit panel estimator so that $c_i \neq 0$. However, this requires the strict exogeneity assumption. In addition, the random-effects Tobit requires the assumption that c_i is uncorrelated with x_{it}. The latter is relaxed in the third version of the model where we follow Wooldridge who presented a modification of the random effects Tobit in spirit of the Chamberlain (1982, 1984) method that allows correlation between u_{it} and c_i. We assume

$$c_i \mid x_i \sim N\left(\psi + \bar{x}_i\xi, \sigma_a^2\right),$$
$$c_i = \psi + \bar{x}_i\xi + a_i$$

so that we estimate a random-effects Tobit model in following modified version

$$y_{it} = \max\left(0, \psi + x_{it}\beta + \bar{x}_i\xi + a_i + u_{it}\right).$$

We can test if $\xi = 0$, and the model would reduce to the traditional random-effects model, where the firm-specific effects are not correlated with the error term.

Table 2 presents the regression results for both firm groups respectively, i.e. RISK = 0 are the routine R&D performers and RISK = 1 are the cutting-edge R&D performers. The first two columns are pooled cross-sectional estimates, the third and fourth are random-effects Tobits that account for unobserved firm-specific heterogeneity in investment behavior under the assumption that the regressors are not correlated with the firm-specific effects. The Wooldridge estimator in columns 5 and 6 relaxes this assumption.

In the pooled cross-sectional model, we find that both groups' investment behavior is affected by the availability of internal funds measured through *PCM*. However, the access to the credit market as measured by the credit rating only restricts the investment of firms with more risky or offensive R&D (RISK = 1). Recall that a larger value of *RATING* indicates a worse rating, and thus the negative sign of the coefficient describes a reduction in R&D with increasing values of the rating.

In the random-effects panel models, we find that the routine R&D performers (RISK = 0) are not subject to credit market constraints as predicted by Kamien and Schwartz (1978). For the offensive R&D performers, the previous results are confirmed. Financial constraints constitute binding restrictions for R&D investment. This model also indicates that there is unobserved heterogeneity in the panel.

The Wooldridge model shows that the assumption of uncorrelatedness between the firm-specific effect and the regressors is rejected: several of the variables' "within" means are individually significant and they are jointly significant altogether. Thus the Wooldridge model is preferable over the standard random effects model. Again, the previous results are confirmed. While credit market restrictions apply to firms conducting cutting edge R&D, they are not binding for routine R&D performers.

Table 3 presents the result of Tobit regression models under a different specification of the rating index we use. Here we define rating classes, where we split this indicator into four categories defined by the quartiles of the rating distribution, so that each group contains 25% of the observations. In the regressions, we now use three dummy variables, B, C and D, where D indicates the worst rating. The group with best ratings, A, serves as reference group.

This is related to the tests Kaplan and Zingales (1997) employed when they rejected the usefulness of investment-cash flow relationships as they did not find a monotonic relationship between cash flow sensitivity and level of constriction. The results from this specification confirm our earlier results, and the models reveal that there strict monotonic relationship between our indicator (*RATING_B, RATING_C, RATING_D*) and R&D investment. Consider the random effects model: the coefficient of rating B amounts to -0.055 indicating that the B group conducts slightly less R&D than the reference group. The coefficient of the C group is -0.155 and the one of the D group equals -0.206. We thus find R&D monotonically decreasing with the level of constriction. The same applies to the pooled cross-sectional estimates. The coefficients are jointly significant in the regressions. Note that it is important to distinguish the heterogeneity of investments in the spirit of Kamien and Schwartz, though. In the group RISK = 0, the ratings' coefficients are all insignificant and they do not show a monotonic relationship. Thus, one would not find convincing results with respect to financial constraints if we had used the full sample without making explicitly a distinction with respect to the heterogeneity of R&D investments, cutting-edge versus routine project.

Note that the Wooldridge model collapses with this specification as there is too much multicollinearity between the rating classes and their within firm means.

Table 2: Tobit regressions on ln(1+R&D), 2642 (1252) obs. for RISK = 0 (RISK = 1)

	Pooled Cross Section Model		**Random-Effects Panel Model**		**Wooldridge Model**	
Variable	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**
ln($EMP_{i,t-1}$)	-0.346***	-0.670***	-0.163**	-0.469 ***	0.269	-0.469 **
	(0.117)	(0.108)	(0.098)	(0.108)	(0.225)	(0.213)
ln($(EMP_{i,t-1})^2$)	0.087***	0.117***	0.067***	0.094 ***	0.010	0.062 ***
	(0.012)	(0.011)	(0.009)	(0.010)	(0.018)	(0.017)
ln((AGE_{it}))	0.027	-0.041	-0.012	-0.031	0.013	-0.039
	(0.036)	(0.036)	(0.034)	(0.041)	(0.143)	(0.156)
$KAPINT_{i,t-1}$	0.556	0.198	0.653***	-0.129	0.717 ***	-0.374
	(0.359)	(0.302)	(0.227)	(0.294)	(0.280)	(0.397)
$PCM_{i,t-1}$	0.580***	0.676***	0.122	0.465 ***	-0.420	0.158
	(0.171)	(0.188)	(0.130)	(0.145)	(0.144)	(0.162)
$RATING_{i,t-1}/100$	0.003	-0.219***	-0.007	-0.196 ***	0.005	-0.160 **
	(0.046)	(0.078)	(0.044)	(0.062)	(0.059	(0.072)
Mean[ln($EMP_{i,t-1}$)]					-0.663 ***	-0.150
					(0.245	(0.249)
Mean[ln($(EMP_{i,t-1})^2$)]					0.082 ***	0.053 **
					(0.020)	(0.021)
Mean[$ln(AGE_{it})$]					-0.041	-0.097
					(0.147)	(0.162)
Mean($KAPINT_{i,t-1}$)					-0.666	0.040
					(0.483)	(0.577)
Mean($PCM_{i,t-1}$)					0.823 ***	1.131 ***
					(0.316)	(0.336)
Mean($RATING_{i,t-1}/100$)					0.006	0.013
					(0.086)	(0.130)
Test on joint significance of time dummies [χ^2 (8)]	47.69***	45.27***	54.48***	41.35***	52.73***	39.33***
Test on joint significance of industry dummies [χ^2 (10)]	123.72***	119.23***	--	--	--	--
Test on joint significance of variable means [χ^2 (6)]	--	--	--	--	39.61***	59.81***
Log-Likelihood	-2,448.27	-1,350.21	-2,175.99	-1,281.35	-2,156.48	-1,252.20
ρ	--	--	0.644	0.545	0.640	0.542

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models).
*** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.

Table 3: Tobit regressions on ln(1+R&D), 2642 (1252) obs. for RISK = 0 (RISK = 1) for *RATING* classes

	Pooled Cross Section Model		Random-Effects Panel Model	
Variable	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**
$\ln(EMP_{i,t-1})$	-0.342***	-0.671***	-0.169*	-0.556 ***
	(0.117)	(0.106)	(0.090)	(0.100)
$\ln(EMP_{i,t-1})^2$	0.087***	0.117***	0.066***	0.103 ***
	(0.012)	(0.010)	(0.008)	(0.010)
$\ln(AGE_{it})$	0.026	-0.047	-0.012	-0.027
	(0.036)	(0.036)	(0.032)	(0.037)
$KAPINT_{i,t-1}$	0.554	0.177	0.739***	0.081
	(0.359)	(0.308)	(0.222)	(0.280)
$PCM_{i,t-1}$	0.564***	0.683***	0.159	0.426 ***
	(0.169)	(0.187)	(0.127)	(0.145)
$RATING_{i,t-1}/100\_B$	0.005	-0.081	0.006	-0.055
	(0.086)	(0.084)	(0.056)	(0.067)
$RATING_{i,t-1}/100\_C$	0.032	-0.225***	0.044	-0.155 **
	(0.092)	(0.092)	(0.065)	(0.077)
$RATING_{i,t-1}/100\_D$	-0.062	-0.255***	-0.049	-0.206 ***
	(0.086)	(0.091)	(0.061)	(0.072)
Test on joint significance of time dummies [χ^2 (8)]	47.46***	45.20***	58.22***	39.62***
Test on joint significance of *RATING* variables [χ^2 (3)]	1.54	10.47**	2.77	10.06 **
Test on joint significance of industry dummies [χ^2 (10)]	124.62***	122.10***	149.74***	104.85***
Log-Likelihood	-2,447.12	-1,348.48	-2,105.36	-1,281.35
ρ	--	--	0.440	0.578

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models). *** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.

4 Conclusions

This paper revisited the discussion on financial constraints for R&D investment. As studies on investment-cash flow relationships have been criticized by Kaplan and Zingales (1997), we suggest to overcome these limitations by using a credit rating index that directly measures the expected level of constriction. Furthermore, we account for the heterogeneity of R&D investments by grouping the sample into potentially constrained and unconstrained firms based on Kamien and Schwartz (1978). They suggest that R&D of a more risky nature will be difficult to finance by external resources where less risky R&D may not be subject to binding financial constraints. We implement this empirically by grouping the sample into routine versus cutting-edge R&D performers. Using panel data, we show that firms pursuing cutting-edge R&D strategies are subject to financial constraints in the credit market. Our indicator, a credit rating index, turns out to curtail R&D spending for cutting-edge R&D while it does not for routine R&D investment.

This finding has important implications for innovation policy. We can assume that cutting-edge innovations are the driving force of technological progress, and thus yield higher social returns than routine R&D projects in the long run. Our results, however, show that such investments are subject to binding credit market constraints. This may call for policy measures towards cutting-edge R&D projects. It would be interesting for further research to investigate whether current policies address those investments. In many European countries, it is current practice that grant proposals for public R&D funding are evaluated with respect to expected economic returns and technological feasibility. It may apply exactly to cutting-edge research, though, that expert reviewers consider daring and visionary projects as not feasible or too uncertain, so that public subsidies may not be granted. If so, projects with potentially high social returns may be judged as inferior to more routine R&D projects.

Finally it should be noted that our study is not without limitations. As we do not have long time-series data for many firms in our sample, we are unable to calculate an R&D stock. This would be necessary to estimate Euler equations or error correction models which are theoretically founded models of investment behavior that map the inter-temporal optimization problem between the size of investments and the level of R&D stocks. While those models have been applied in many studies, we can only use their ingredients, but have to depart with the specification from the theory-grounded choice due to data restrictions.

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Appendix

Table A.1: Distribution of NOVEL in the sample

Share of sales with market novelties	Relative Frequency	Cumulative relative frequency
0	37%	37%
(0 – 2.5%]	15%	52%
(2.5% – 5%]	15%	67%
(5% - 7.5%]	7%	74%
(7.5% - 10%]	6%	80%
(10% - 15%]	8%	88%
more than 15%	12%	100%
	100%	

The regressions discussed in the text of the paper define the upper 33% of the distribution (cut-off at 5%) as cutting-edge R&D performers. The following tables A.2 and A.3 use (about) the upper quartile (cut-off at 7.5%) of NOVEL as cutting-edge R&D performers. As further check, we defined the cut-off at (about) the median of the distribution with NOVEL at 2.5%. See Tables A.4 and A.5. All results discussed with the other specification remain robust.

Table A.2: Tobit regressions on ln(1+R&D), 2913 (981) obs. for RISK = 0 (RISK = 1) with *NOVEL*-split at 7.5%

Variable	**Pooled Cross Section Model** Risk = 0	Risk = 1	**Random-Effects Panel Model** Risk = 0	Risk = 1	**Wooldridge Model** Risk = 0	Risk = 1
ln($EMP_{i,t-1}$)	-0.372***	-0.709***	-0.168*	-0.544 ***	0.151	-0.376 **
	(0.108)	(0.115)	(0.091)	(0.121)	(0.209)	(0.215)
ln$(EMP_{i,t-1})^2$	0.089***	0.122***	0.067***	0.100 ***	0.019	0.053 ***
	(0.011)	(0.011)	(0.008)	(0.011)	(0.016)	(0.018)
ln(AGE_{it})	0.001	0.010	-0.029	-0.010	0.014	0.010
	(0.033)	(0.042)	(0.032)	(0.045)	(0.134)	(0.167)
$KAPINT_{i,t-1}$	0.455	0.400	0.511**	0.110	0.548 ***	-0.079
	(0.328)	(0.351)	(0.220)	(0.313)	(0.279)	(0.389)
$PCM_{i,t-1}$	0.655***	0.781***	0.150	0.501 ***	-0.075	0.238
	(0.165)	(0.199)	(0.127)	(0.146)	(0.142)	(0.157)
$RATING_{\,i,t-1}/100$	-0.019	-0.251***	-0.036	-0.189 ***	0.023	-0.171 **
	(0.045)	(0.080)	(0.042)	(0.069)	(0.055)	(0.080)
Mean[ln($EMP_{i,t-1}$)]					-0.514 ***	-0.429
					(0.230)	(0.259)
Mean[ln$(EMP_{i,t-1})^2$]					0.069 ***	0.080 **
					(0.019)	(0.022)
Mean[$ln(AGE_{it})$]					-0.058	-0.053
					(0.138)	(0.627)
Mean($KAPINT_{i,t-1}$)					-0.468	-0.173
					(0.455)	(0.627)
Mean($PCM_{i,t-1}$)					1.025 ***	1.037 ***
					(0.301)	(0.353)
Mean($RATING_{i,t-1}/100$)					0.012	0.060
					(0.082)	(0.143)
Test on joint significance of time dummies [χ^2 (8)]	55.26***	25.31**	68.23***	26.44***	68.42***	24.09***
Test on joint significance of industry dummies [χ^2 (10)]	134.93***	125.78***	--	--	--	--
Test on joint significance of variable means [χ^2 (6)]	--	--	--	--	43.93***	66.79***
Log-Likelihood	-2,787.37	-1,009.15	-2,507.57	-947.10	-2,485.92	-914.85
ρ	--	--	0.624	0.588	0.640	0.584

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models).
*** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.

Table A.3: Tobit regressions on ln(1+R&D), 2913 (981) obs. for RISK = 0 (RISK = 1) for *RATING* classes with *NOVEL*-split at 7.5%

	Pooled Cross Section Model		**Random-Effects Panel Model**	
Variable	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**
$\ln(EMP_{i,t-1})$	-0.383***	-0.712***	-0.213*	-0.588 ***
	(0.108)	(0.115)	(0.084)	(0.110)
$\ln(EMP_{i,t-1})^2$	0.090***	0.123***	0.069***	0.107 ***
	(0.011)	(0.011)	(0.008)	(0.010)
$\ln(AGE_{it})$	-0.005	-0.013	0.044	-0.010
	(0.034)	(0.042)	(0.030)	(0.040)
$KAPINT_{i,t-1}$	0.446	0.377	0.608***	0.367
	(0.330)	(0.361)	(0.215)	(0.298)
$PCM_{i,t-1}$	0.641***	0.804***	0.195	0.487 ***
	(0.162)	(0.200)	(0.124)	(0.145)
$RATING_{i,t-1}/100\_B$	0.008	-0.043	0.006	-0.005
	(0.078)	(0.090)	(0.046)	(0.070)
$RATING_{i,t-1}/100\_C$	-0.026	-0.187***	-0.005	-0.098
	(0.083)	(0.099)	(0.062)	(0.081)
$RATING_{i,t-1}/100\_D$	-0.120	-0.247***	-0.099*	-0.194 ***
	(0.080)	(0.092)	(0.058)	(0.074)
Test on joint significance of time dummies [χ^2 (8)]	55.31***	25.57***	71.91***	24.26***
Test on joint significance of *RATING* variables [χ^2 (3)]	3.89	9.37**	4.68	9.42**
Test on joint significance of industry dummies [χ^2 (10)]	136.57***	126.31***	165.05***	96.49***
Log-Likelihood	-2,784.63	-1,009.48	-2,430.09	-906.04
ρ	--	--	0.555	0.477

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models). *** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.

Table A.4: Tobit regressions on ln(1+R&D), 2068 (1826) obs. for RISK = 0 (RISK = 1) with *NOVEL*-split at 2.5%

	Pooled Cross Section Model		**Random-Effects Panel Model**		**Wooldridge Model**	
Variable	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**
$\ln(EMP_{i,t-1})$	-0.361***	-0.682***	-0.200*	-0.482 ***	0.280	-0.382 **
	(0.132)	(0.100)	(0.111)	(0.098)	(0.262)	(0.192)
$\ln(EMP_{i,t-1})^2$	0.089***	0.117***	0.070***	0.094 ***	0.003	0.059 ***
	(0.013)	(0.010)	(0.010)	(0.009)	(0.021)	(0.016)
$\ln(AGE_{it})$	0.018	-0.024	-0.005	-0.022	-0.118	0.158
	(0.043)	(0.032)	(0.041)	(0.033)	(0.176)	(0.132)
$KAPINT_{i,t-1}$	0.654	0.347	0.628**	0.138	0.624 *	0.094
	(0.420)	(0.277)	(0.277)	(0.240)	(0.351)	(0.309)
$PCM_{i,t-1}$	0.413*	0.755***	0.009	0.432 ***	-0.134	0.174
	(0.212)	(0.159)	(0.054)	(0.119)	(0.184)	(0.132)
$RATING_{i,t-1}/100$	-0.031	-0.167***	0.011	-0.147 ***	-0.062	-0.140 **
	(0.057)	(0.062)	(0.054)	(0.047)	(0.077)	(0.056)
Mean[$\ln(EMP_{i,t-1})$]					-0.764 ***	-0.443
					(0.283)	(0.224)
Mean[$\ln(EMP_{i,t-1})^2$]					0.098 ***	0.053 ***
					(0.023)	(0.019)
Mean[$ln(AGE_{it})$]					0.100	-0.202
					(0.182)	(0.136)
Mean($KAPINT_{i,t-1}$)					-0.659	-0.232
					(0.578)	(0.481)
Mean($PCM_{i,t-1}$)					0.617	1.140 ***
					(0.389)	(0.283)
Mean($RATING_{i,t-1}/100$)					-0.056	0.050
					(0.107)	(0.096)
Test on joint significance of time dummies [χ^2 (8)]	29.37***	62.72***	37.56***	55.67***	33.57***	57.62***
Test on joint significance of industry dummies [χ^2 (10)]	92.54***	148.46***	--	--	--	--
Test on joint significance of variable means [χ^2 (6)]	--	--	--	--	38.43***	62.65***
Log-Likelihood	-1,802.32	-1,944.28	-1,622.38	-1810.84	-1,603.52	-1780.15
ρ	--	--	0.624	0.589	0.614	0.583

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models).
*** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.

Table A.5: Tobit regressions on ln(1+R&D), 2068 (1826) obs. for RISK = 0 (RISK = 1) for *RATING* classes with *NOVEL*-split at 2.5%

	Pooled Cross Section Model		**Random-Effects Panel Model**	
Variable	**Risk = 0**	**Risk = 1**	**Risk = 0**	**Risk = 1**
$\ln(EMP_{i,t-1})$	-0.376***	-0.688***	-0.204**	-0.542 ***
	(0.132)	(0.101)	(0.103)	(0.190)
$\ln(EMP_{i,t-1})^2$	0.090***	0.118***	0.070***	0.100 ***
	(0.014)	(0.010)	(0.010)	(0.008)
$\ln(AGE_{it})$	-0.009	-0.031	0.012	-0.001
	(0.422)	(0.032)	(0.038)	(0.030)
$KAPINT_{i,t-1}$	0.626	0.349	0.710***	0.365
	(0.330)	(0.279)	(0.272)	(0.231)
$PCM_{i,t-1}$	0.422**	0.759***	0.195	0.435 ***
	(0.209)	(0.158)	(0.124)	(0.118)
$RATING_{i,t-1}/100\_B$	0.091	-0.082	0.101	-0.005
	(0.106)	(0.073)	(0.072)	(0.070)
$RATING_{i,t-1}/100\_C$	0.014	-0.152**	0.043	-0.098
	(0.114)	(0.074)	(0.082)	(0.081)
$RATING_{i,t-1}/100\_D$	-0.023	-0.243***	-0.019	-0.194 ***
	(0.106)	(0.072)	(0.077)	(0.074)
Test on joint significance of time dummies [χ^2 (8)]	30.24***	63.07***	42.26***	55.40***
Test on joint significance of *RATING* variables [χ^2 (3)]	1.65	12.24***	3.17	13.35**
Test on joint significance of industry dummies [χ^2 (10)]	91.95***	149.29***	102.22***	144.71***
Log-Likelihood	-1,801.17	-1,941.69	-1,572.75	-1,746.75
ρ	--	--	0.552	0.494

Notes: All models include an intercept (not presented). Standard errors in parentheses (clustered in pooled cross-sectional models). *** (**, *) indicate a significance level of 1% (5 ,10%). ρ indicates the share of the total variance which is due to the cross-sectional variation.